

Skill-Aware Task Assignment in Crowdsourcing Applications

Panagiotis Mavridis
University of Rennes 1
panagiotis.mavridis@irisa.fr

David Gross-Amblard
University of Rennes 1
david.gross-amblard@irisa.fr

Zoltán Miklós
University of Rennes 1
zoltan.miklos@irisa.fr

Abstract

Besides simple human intelligence tasks such as image labeling, crowdsourcing platforms propose more and more tasks that require very specific skills. In such a setting we need to model skills that are required to execute a particular job. At the same time in order to match tasks to the crowd, we have to model the expertise of the participants. We present such a skill model that relies on a taxonomy. We also introduce task assignment algorithms to optimize the result quality. We illustrate the effectiveness of our algorithms and models through preliminary experiments with synthetic datasets.

I. INTRODUCTION

Crowdsourcing platforms such as Amazon Mechanical Turk¹, Crowdfunder² or FouleFactory³ engage more than 500k participants [5] who perform tasks on a daily basis. While one can obtain useful results for a number of tasks (that would be otherwise difficult for computers), managing the quality of the results is a serious issue. In particular, in cases where a specific expertise is needed (to complete a given task), the platform should assign the task to a participant who has this skill.

Skill models and their use in the context of crowdsourcing has already been identified as an important tool for improving the result quality. For instance, Bozzon et al. [2] extract knowledge about participants of social platforms, and use unstructured labels (or tags) with associated probabilities to represent participant skills. Using a similar simple flat skill model, Roy et al. [4] propose a generic task assignment algorithm.

Beyond the flat modeling of skills, the use of structured skills can be considered to allow forms of reasoning (such as “the skill *English writer* is more specific than *English reader*”). In their vision paper, Maary et al. [3] propose to model skills using a taxonomy or an ontology. They argue that it could provide better results than classical quality assurance techniques such as spammer detection. But being a vision paper, no algorithmic counterpart is provided. Amsterdamer et al. [1] also rely on an ontology to model a crowd, but they take a different perspective. Their goal is to extend a knowledge base by focusing questions to relevant crowd members (“mining the crowd”). This approach is distinct from task assignment, where every task has to be assigned to a participant, even if his/her skills are not perfectly relevant.

In the current poster we examine a novel model of skill representation based on taxonomy along with algorithms for task assignment. We define the skill of a participant and the required skill of a task as a set of nodes in a given skill taxonomy. We then consider and formalize the optimization problem of task assignment to most suitable participants. In the experimentation section we show how our model performs in comparison with random assignments.

¹<https://www.mturk.com>

²<http://www.crowdfunder.com>

³<http://www.foulefactory.com>

II. MODEL

In this work, we made several initial assumptions. First we suppose that a skill taxonomy is available. Several such taxonomies are already in use, such as ESCO⁴, with a total of 5,000 concepts. We suppose that the skills required to fulfill a task are explicitly stated by the requester, and that participants provide the list of skills they have with respect to the taxonomy (such painful annotations could also be estimated, but this is out of the scope of the present work). In the sequel we restrict our attention to task requiring a single skill, as such tasks are more adapted for crowdsourcing. as a complex task can be split into several, simple ones. On the contrary, a participant can declare several skills. We neglect spammers for the sake of simplicity, as they can be ruled out by well-known crowd management techniques, such as majority voting or participant response-quality estimation based on a test set. Finally, we focus our attention to participative platforms, where tasks are performed for free. In such platforms, participants are specially sensitive to the mapping of tasks with respect to their skill profiles.

Let $T = \{t_1, t_2, \dots\}$ be a set of tasks and $P = \{p_1, p_2, \dots\}$ be a set of participants. Let $S = (\{s_1, s_2, \dots\}, \leq)$ be a skill taxonomy, i.e. a tree where s_1, s_2, \dots denote elementary skills and \leq is the partial order within skills. For example, if $s = \text{Basic Java Programming}$ and $s' = \text{Java 1.8 Thread Programming}$, then $s \leq s'$. This means that any participant with skill s' can perform a task requiring skill $s \leq s'$. We denote the skill that is required for a task t by a node $skill(t) \in S$, and the set of skills of a participant p by $skill(p) \in S$. Given a set of tasks and participants, a task assignment \mathcal{A} is a mapping from T to P , that maps a task $t \in T$ to $\mathcal{A}(t) = p \in P$. A task assignment is partial (some tasks may not be assigned) and injective (a participant can only perform one task during this assignment).

We next model the quality of an assignment. The best situation is to map a task with required skill s to a participant with this exact skill. Note also that a participant with a more specialized skill $s' > s$ can perform the task. If such skills are not available in the crowd, more generic participants can be used, but at the expense of a lower quality. In order to capture these situations, we consider a *skill distance* between the required skill and the available ones, inspired by classical Resnik similarity. Let $depth(s)$ be the depth of s in the taxonomy S , and d_{max} be the maximum depth of S . Let $lca(s, s')$ be the least common ancestor of s and s' in the taxonomy. Then the *skill distance* is $d(s, s') = \frac{d_{max} - depth(lca(s, s'))}{d_{max}}$ and the distance between a task t and a participant p is given by

$$D(t, p) = \begin{cases} 0 & \text{if } \exists s \in skill(p) \text{ s.t. } s \geq skill(t), \\ \min_{s \in skill(p)} d(skill(t), s) & \text{otherwise.} \end{cases}$$

⁴ESCO: European Skills, Competences Qualifications and Occupations. <https://ec.europa.eu/esco/home>.

With these definitions, the distance is 0 if a participant has the required skill or he/she is more specialized. Otherwise it depends on the distance between the task skill and the best available participant skill. It is noteworthy that d and D are not metric distances. Finally, the *cumulative distance* $\mathcal{D}(\mathcal{A})$ of an assignment \mathcal{A} is the weighted sum of distances of participants, weighted by the number of participants at this distance, i.e.: $\mathcal{D}(\mathcal{A}) = \sum_{i=0}^{\infty} i * N_i$, where N_i is the number of participants assigned to a task t at distance i . The *normalized cumulative distance* is $\mathcal{D}(\mathcal{A})$ divided by the total number of assigned participants. Finding a best assignment is then finding an \mathcal{A} such that $\mathcal{D}(\mathcal{A})$ is minimized.

III. ALGORITHMS

As a baseline, we consider the RANDOM and the EXACTTHENRANDOM algorithm. The first performs a random assignment of tasks to participants while the second performs the exact matches first and a random assignment for the remaining tasks. We approximate the optimal solution with two heuristic algorithms. In MATCHPARTICIPANTFIRST, we see the skills of tasks as a set of words, each word denoting a path in the taxonomy. We reverse-sort these words alphabetically, hence the more specific skills of each branch of the taxonomy appear first. We also reverse-sort participants according to their number of skills, so that the more diverse participants appear first. Then, for each sorted task skill, and for each distance, starting from 0, we scan the list of sorted participants and assign the task to the first available participant at this distance. We go on with increasing distances until there is no task or participant left.

In MATCHPROFILEFIRST, we sort the tasks as in the MATCHPARTICIPANTFIRST. We also reverse-sort all the participant skills alphabetically. Then, for each sorted skill, and for each distance, starting from 0, we scan the list of sorted participant skills and assign the task to the first available skill (hence participant) at this distance. Again, we go on with increasing distances until there is no task or participant left.

IV.

PRELIMINARY RESULTS AND CONCLUSION

We generated various synthetic datasets. For the first experiment, a taxonomy with 10 children at each node and depth 10 was used. A number of 1,000 tasks with a random skill were generated. A number of 1,000 participants were generated using a budget technique: a participant can learn random skills up to a given budget. Figure 1 shows that (1) the cumulative distance of both our algorithms are similar, and that both outperform the EXACTTHENRANDOM assignment in terms of quality; (2) the cumulative distance is smaller when participants have more specific skills (higher skill budget).

For the second experiment a set of 3,000 tasks and 3,000 participants were generated respecting the same taxonomy as before. Figure 2 shows that (1) the percentage of participants assigned by both our algorithms are similar, and that both outperform the EXACTTHENRANDOM assignment in terms of quality; (2) EXACTTHENRANDOM tends to sacrifice a lot of good participants to distant participants, while better assignments are available.

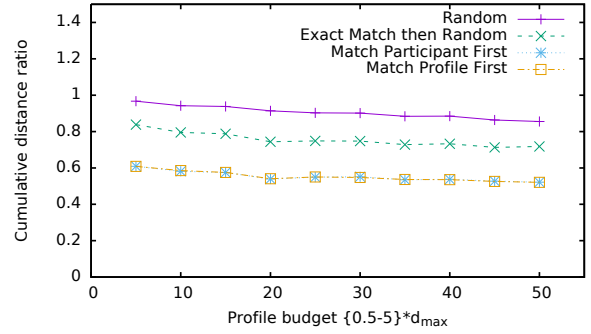


Figure 1: Assignment quality with respect to participant budget

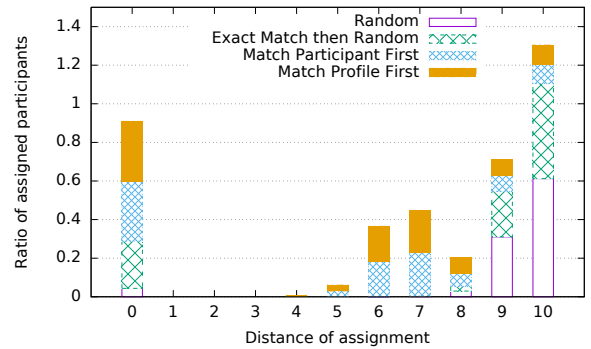


Figure 2: Ratio of participants assigned per distance

These preliminary results show the significant gain we obtain with the help of taxonomy aided assignment compared to a random or partial random assignment. In future work we will investigate algorithms based on indexing or hashing of skills, and relax the skill model with probabilities.

REFERENCES

- [1] Yael Amsterdamer, Susan B. Davidson, Tova Milo, Slava Novgorodov, and Amit Somech. OASSIS: query driven crowd mining. In *International Conference on Management of Data, SIGMOD 2014, Snowbird, UT, USA, June 22-27, 2014*, pages 589–600, 2014.
- [2] Alessandro Bozzon, Marco Brambilla, Stefano Ceri, Matteo Silvestri, and Giuliano Vesci. Choosing the right crowd: Expert finding in social networks. In *Proceedings of the 16th International Conference on Extending Database Technology, EDBT '13*, pages 637–648, 2013.
- [3] KindaEl Maarry, Wolf-Tilo Balke, Hyunsouk Cho, Seung-won Hwang, and Yukino Baba. Skill ontology-based model for quality assurance in crowdsourcing. In *Database Systems for Advanced Applications, Lecture Notes in Computer Science*, pages 376–387. Springer Berlin Heidelberg, 2014.
- [4] Senjuti Basu Roy, Ioanna Lykourantzou, Saravanan Thirumuruganathan, Sihem Amer-Yahia, and Gautam Das. Optimization in knowledge-intensive crowdsourcing. *CoRR*, abs/1401.1302, 2014.
- [5] Dahn Tamir. 500 000 worldwide mechanical turk workers. In *techlist*, Retrieved September 17, 2014.